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FUSING IMAGING SPECTROMETRY AND AIRBORNE LASER SCANNING DATA FOR TREE SPECIES DISCRIMINATION

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ABSTRACT

Accurate mapping of tree species composition within forest ecosystems is an important aspect of management planning and monitoring. Passive optical remote sensing in general and imaging spectroscopy (IS) in particular have played an important role in producing such maps, but are suffering from issues due to vegetation structure. On the other hand, the structural information provided by airborne laser scanning (ALS) was shown to be helpful for species discrimination, particularly in heterogeneous forests. In this paper, we investigate the potential of product-level fusion of IS and ALS to provide a better tree species differentiation based on their complementarity. Our results show that the fused tree species map does improve on the single system maps and more accurately provides the distribution and fraction of each tree species within the study area.

Index Terms— data fusion, airborne laser scanning, imaging spectrometry, tree species, support vector machines.

1. INTRODUCTION

Assessing and quantifying forest ecosystem goods and services (associated with water refinement, carbon sequestration, biodiversity, or wildlife habitats) and their underlying processes helps to develop sustainable management strategies and to project biogeochemical cycles under changing climate conditions [1, 2]. Particularly the tree species composition is an important aspect of forest monitoring and is as well relevant for management planning. Assessing the tree species composition with traditional fieldwork is labor-intensive, time-consuming and mostly limited by spatial extent; on the other hand, remote sensing data has the potential to overcome these limitations.

Although different tree species often have unique spectral signatures at leaf level, mapping based on spectral reflectance properties alone is often an ill-posed problem, since the spectral signature of the canopy is influenced by tree age, canopy gaps, shadows and forest floor characteristics [3]. Thus, reducing the unknowns by including structural characteristics of different species (e.g. branching and foliage distribution) should improve determination procedures [4].

ALS is an established tool to estimate forest structural parameters in both horizontal and vertical directions due to the penetration of the transmitted laser signal through the vegetation canopy [5].

Consequently, the goal of this study is to investigate the capabilities of fusing ALS-derived structural parameters and ordinary IS data to discriminate different tree species.

2. STUDY AREA AND DATA

For this study, an area (300×300 m) of a semi-natural forest in Laegeren, Switzerland (47°28'N, 8°21'E), was selected for this study. This deciduous-dominated forest contains a high diversity of species and ages, from 55 to 160 years old (Eugster et al., 2007) and is located on steep hills (slope up to 60°). Tree species data were collected during a comprehensive forest inventory campaign, in which more than 1300 trees were assessed and more than eight species types were recognized from the trunk bark during early spring 2013. The dominant species, in order of abundance, are: *fagus sylvatica, fraxinus excelsior, acer pseudoplatanus, abies alba, picea abies, ulmus glabra* and *acer platanoides*. In addition, the dead trees (mostly deciduous) were included in this inventory. Tree location, direction and amount of the crown displacement in relation to its trunk, social status and approximate crown dimensions have been measured as well.

Two small footprint, full-waveform ALS systems were used to survey the study area under both leaf-on (01.08.2010) and leaf-off (10.04.2010) conditions [6].

Spectral information has been acquired by the Airborne imaging spectrometry Prism Experiment (APEX, [7]) sensor in 301 spectral bands (400 - 2500 nm) and 2 m spatial resolution. Furthermore, we employed a very light drone (Sensefly eBee) to generate high spatial resolution aerial orthophotos of the area in four channels (NIR and visible) during the autumn 2013. These data facilitate the coupling of the forest inventory data to the other remotely sensed data.

3. METHODOLOGY

An empirical fusion approach at product-level was applied in order to make best use of the complementarities of ALS and IS data and to overcome the complexity of the heterogeneous forest scene [8].

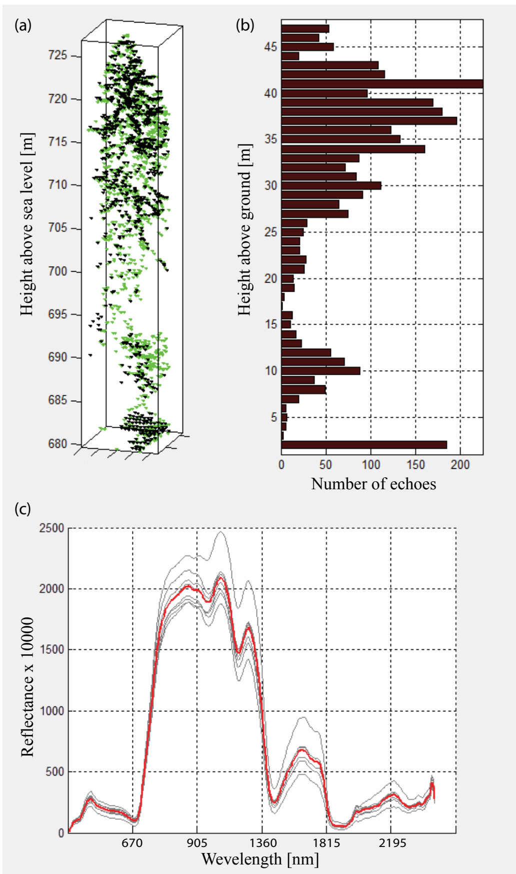

Figure 1. A sample of delineated ITCs; a) leaf on/off point cloud; b) vertical distribution of LiDAR echoes; c) spectral signature of eight sunlit pixels from total 21 pixels inside the ITC.

3.1. Pre-processing

Following radiometric and atmospheric corrections, IS reflectance data were thoroughly ortho-rectified using the ALS provided Digital Surface Model, so that misalignment differences remained at less than half the size of the IS data pixel size (approximately ±1 m).

Using the ALS-derived canopy height and based on the forest definition in Switzerland [9], all the areas below 3 m were assigned as non-forest in both ALS and IS data. In addition, since consideration of spectral information from both sunlit and shaded parts of tree crowns deteriorates species classification accuracy [10], a shaded/sunlit mask was generated from the ALS point cloud, using a ray tracing approach. The mask was applied on the hyperspectral image cube to remove shaded pixels.

3.2. Coupling the forest inventory and remote sensing data

Because of the leaning of tall trees in slopes, linking forest inventory data with remote sensing data faces difficulties in our study area. Inevitable errors in tree locating on the ground also contribute to this problem. Consequently, the high resolution aerial images acquired by the drone were automatically segmented to individual tree crowns (ITCs) by using Definiens Developer software (version 7.0) [11]. Visual interpretation was carried out to refine and modify final tree crowns. Since the data were taken in autumn with beginning discoloration, was possible, due to leaf senescence. Neighbouring ITCs, with a high probability of matching the measured tree in the field, were subsequently selected based on a set of constraints (e.g. considering the upper crown layers only).

3.3. Structural and spectral features

A variety of spectral and structural features were used to improve species discrimination accuracy [12, 13]. Although a few band selection algorithms (e.g. forward feature selection) were tested, we used 50 first principle components (PCs) of IS data to ensure the most relevant spectral information was kept.

Regarding the ALS data, structurally related statistics along the vertical direction were derived from full-waveform data. The histograms of the vertical echo distribution (percentage of echoes per vertical bin) and the related full-waveform properties (echo width, amplitude, intensity) were analyzed to define canopy structural features (i.e. for each vertical bin the statistics mean, maximum, minimum and standard deviation of the specific attribute were calculated).

Since the available ALS data has a very high point density (>25 point/m2), we were able set the vertical dimension of the histogram bins to 1 m, however, 2 m x 2 m horizontal dimensions have been used to match the spatial resolution of IS dataset.

3.4. Classification

A nonlinear support vector machine (SVM) classifier has been deployed for distinguishing the eight most prevalent tree species in our study area. SVMs are proved to be an advantage for classifying high dimensional multiple sources data [14]. The spatially explicit information layers, containing both, the spectral and structural components from the IS and ALS datasets, were then combined together in the pixel-based image classification procedure.

4. RESULTS AND DISCUSSION

4.1 Species samples

Due to the inability of aerial photographs to reveal suppressed trees, particularly in dense forests, only 980 ITCs were delineated using the semi-automatic approach, whereas 1308 individual trees were measured in the field. Nevertheless, coupling this dataset with forest inventory data provided the necessary reference data for classification (Table 1). Each candidate ITC for training and validation was subsequently inspected spectrally and spatially to ensure that influences of external components (e.g. understory) are minor (Figure 1).

Table 1. Ground reference samples collected by a semi-automatic approach and field measurements.

No	Species name	Delineated ITCs		Field measurements
		Training	Validation	
1	*dead tree (deciduous)*	6	3	30
2	*abies alba*	25	13	108
3	*picea abies*	19	10	51
4	*acer platanoides*	7	3	40
5	*acer pseudoplatanus*	9	6	168
6	*fagus sylvatica*	31	12	515
7	*fraxinus excelsior*	25	22	248
8	*ulmus glabra*	5	3	43
	Total	127	72	1203

4.2. ALS-derived structural features

Structural features were derived based on the vertical distribution of the ALS echoes and their waveform characteristics. Using the derived histograms, we determined the amount of clearly separable canopy layers such as understory and top crown layer as well as the percentage of echoes per each detected layer. For each grid cell we calculated additionally the two following structure variables: first, the ratio of ground returns to canopy returns based on leaf-on data only, which ground returns are all returns less than 3 m above ground and canopy returns are all returns greater than 3 m above ground, and second, the percentage difference of canopy returns of the leaf-on acquisition to the leaf-off acquisition. Adding the ALS-derived intensity distribution in vertical direction, 20 structure related features were entirely provided for the subsequent analysis of species differentiation.

4.3. Classification

Three datasets include 20 ALS-derived features, first 50 IS-derived PCs and combined ALS and IS features (70 layers) were classified using a nonlinear SVM classifier (with a radial basis kernel function). The accuracy of the tree species classification was evaluated by analysis of the confusion matrix (Table 2). Resulted overall accuracies show 30.2 percent improvement for fused data rather than ALS data solely. Whereas, only 3.5 percents increase was achieved by adding ALS features to IS data. Although this slight improvement may sound unremarkable, but considering other components of confusion matrix reveals larger improvements. Considering user’s and producer’s accuracies for classified species, Table 2 shows:

- Both accuracy components were significantly increased for the coniferous species (2, 3) and dead trees; wherein structure of these species clearly differs from other species.
- We also observed an accuracy improvement for most deciduous species except for acer pseudoplatanus.
- Since both acer species (4, 5) do not generally place in the top layers in our study area, discrimination of the relevant crowns in remote sensing data needs more training samples.

Table 2. Comparison of SVM classification accuracies resulting from ALS, IS and fused ALS and IS datasets. Bold values indicate improvement in the fused dataset, italic value a decrease in classification accuracy.

No.		ALS	IS	Fused ALS and IS
	Overall	60.6	87.3	**90.8**
	Kappa	0.44	0.83	**0.87**
1	Producer’s	9.1	95.5	**98.5**
	User's	85.7	96.9	**100.0**
2	Producer’s	74.0	93.4	**100.0**
	User's	61.9	85.1	**100.0**
3	Producer’s	42.3	81.3	**95.6**
	User's	59.3	87.0	**97.4**
4	Producer’s	0.0	17.1	**20.3**
	User's	0.0	63.6	**83.3**
5	Producer’s	7.6	61.3	*54.3*
	User's	84.2	92.2	*83.9*
6	Producer’s	95.1	98.4	**99.5**
	User's	57.1	91.2	*85.1*
7	Producer’s	20.0	92.6	**97.0**
	User's	88.9	81.6	**94.4**
8	Producer’s	49.4	90.0	**100.0**
	User's	71.0	90.0	**90.9**

5. CONCLUSION

The final tree species map improved on the single system products and provides the distribution and fraction of each tree species within our forest site. A thorough accuracy analysis for each species reveals that not all tree species could be discriminated with high accuracy; however, the overall accuracy is improved using the fusion approach. Nevertheless most of the species profit from product-level fusion based on the exhaustive structural and spectral feature set for its discrimination. User's and producer's accuracies analysis also confirms superior performance for each species when the fused data has been used. Nonetheless, there are still limitations, particularly in dense deciduous dominated forest areas, where the individual crowns are intersecting and prevent an unambiguous assignment of a specific tree species.

5. ACKNOWLEDGEMENTS

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